International Journal of Research in Industrial Engineering

www.riejournal.com

Int. J. Res. Ind. Eng. Vol. 14, No. 1 (2025) 177–195.

Paper Type: Research Paper

Designing Supply Chain of Blood Under Uncertainty: A Case Study

Ali Namazian[1,*], Reza Babazadeh[2]

[1] Department of Industrial Engineering, Faculty of Engineering, University of Kashan, Kashan, Iran; a.namazian@kashanu.ac.ir.

[2] Department of Industrial Engineering, Faculty of Engineering, Urmia University, Urmia, Iran; r.babazadeh@urmia.ac.ir.

Citation:

Received: 19 Januray 2024 *Revised: 21 March 2024* *Accepted: 06 April 2024*	Namazian, A., & Babazadeh, R. (2025). Designing supply chain of blood under uncertainty: A case study. *International journal of research in industrial engineering*, *14*(1), 177-195.

Abstract

Ensuring an adequate and healthy blood supply is a persistent challenge that healthcare systems worldwide face. The need for blood donors and their products is constant, while the supply from donors is somewhat irregular, and the demand for these products is often unpredictable. Furthermore, the levels of demand and blood donation are uncertain. As a result, uncertainty plays a crucial role in the blood supply chain, especially during crises such as earthquakes and pandemics. In this regard, designing the Blood Supply Chain Network (BSCN) under uncertainty is essential for meeting fluctuating demand, addressing logistical challenges, responding to emergencies, and ensuring the quality and safety of blood products throughout the supply chain. This research aims to present a Mixed-Integer Linear Programming (MIP) model under uncertainty for strategic and tactical decision-making in the blood supply chain over a determined planning horizon. The fuzzy theory approach has been used to incorporate uncertainty into the model's parameters. An interactive fuzzy solution approach based on credibility measurement has been developed to solve the fuzzy optimization model. The results obtained from designing and implementing the proposed model in a case study indicate the desirable efficiency of this model in determining the optimal number and location of facilities in a BSCN, including fixed facilities, temporary facilities, and blood banks, as well as the optimal amount of blood transfer between different entities of the blood supply chain. Furthermore, a sensitivity analysis of the parameters is performed to determine the most influential factors affecting the objective function of the problem.

Keywords: Blood supply chain, Healthcare systems, Uncertainty, Mixed-integer linear programming model.

1 | Introduction

Healthy blood is crucial for sustaining life, as it performs essential functions like carrying oxygen, nutrients, and removing waste products from our cells. Every second, across all regions of the world, people of different

Corresponding Author: a.namazian@kashanu.ac.ir

https://doi.org/10.22105/riej.2024.436665.1415

ages, races, and backgrounds require blood transfusions to manage conditions like surgeries, trauma, childbirth complications, and chronic illnesses such as anemia or cancer. Blood transfusions can mean the difference between life and death, emphasizing the need for a consistent and reliable blood supply. The demand for safe, healthy blood is universal, highlighting the vital role of blood donation in modern healthcare systems worldwide. In this respect, the blood supply chain is a critical component of the healthcare system, playing a vital role in enhancing efficiency and reducing costs across the health sector [1]. The healthcare sector has the most complex supply chains compared to other industries [2]. On the other hand, human blood differs from regular commodities because its demand is highly unpredictable [3]. Humans have always faced various types of natural disasters and catastrophes. COVID-19, as a pandemic, has negatively impacted the blood supply chain by drastically reducing blood donation [4]. Despite remarkable advancements in medical science, there is still no artificial substitute for blood, and only blood donated by kind-hearted individuals can save lives from death.

Blood shortages impose significant costs on society and can lead to increased mortality rates [5]. Thus, proper management of blood and its derivatives is considered one of the most important issues in the healthcare system, and this has been studied by many researchers [6–9]. The blood supply chain manages blood flow from donor to patient, ensuring patients' needs are met.

Given the uncertain factors such as fluctuations in blood demand, potential facility disruptions, and the perishable nature of blood products, managing blood supply chains under conditions of uncertainty is critical [10]. Careful advance planning of the blood supply chain is extremely important due to the numerous activities that must be meticulously coordinated to ensure demand is met [11]. Perishability, the short lifespan of blood components, and unpredictability in demand quantities make managing the blood supply chain more complex. Therefore, developing an appropriate blood network model is essential to address uncertainty and minimize patient delivery time [12].

Besides being collected at temporary and permanent collection sites, blood is sent to blood centers for testing and processing. A primary objective addressed in existing literature models for the blood supply chain is determining the optimal locations for temporary collection centers to ensure efficient and cost-effective demand fulfillment [13].

To the best of our knowledge, there is currently no comprehensive design of a Blood Supply Chain Network (BSCN) that determines the optimal number and location of network components and the optimal flow of blood transfusion while considering the uncertain parameters of the network and the perishability of blood products. This research proposes a Mixed-Integer Linear Programming (MIP) model under uncertainty for strategic and tactical decision-making in blood collection systems over the planning horizon. This model determines the optimal number and location of components in the blood supply network, which include donor groups, fixed facilities, temporary facilities, blood banks, and procurement and processing centers. Fixed collection locations such as hospitals and temporary locations such as containers and mobile blood collection buses have been considered. The fuzzy theory approach has been used to model the problem under conditions of uncertainty. An interactive fuzzy solution approach based on the extended credibility measure is developed to solve the fuzzy optimization model.

On the other hand, the perishability of blood is an important factor of the model, meaning that blood cannot be stored for a long period. Therefore, to address the blood storage issue, we decomposed blood products into six groups: whole blood, packed red blood cells, washed red blood cells, frozen red blood cells, platelets, and plasma. This categorization aims to extend the storage duration by exploring solutions and implementing efficient methods.

Additionally, in this research, it is possible to import and export various blood products. It was implemented in Urmia, Iran, as a case study to validate the proposed model and design its optimal BSCN. Considering the respective network, after blood collection, it is transferred to the blood bank for testing and analysis. Blood products are then prepared in the procurement and processing centers. In the event of a blood shortage in

the blood bank, importing from neighboring provinces is possible. Additionally, if neighboring provinces require blood, it will be exported to them, generating income.

2 | Literature Review

The blood supply chain poses unique challenges that require careful consideration and optimization. This supply chain is critical to managing blood flow and its components, addressing perishability, donor availability, demand uncertainty, and efficient distribution. Researchers and practitioners often focus on developing models and strategies to enhance the blood supply chain's efficiency, resilience, and overall performance. Previous studies have approached the design problem of the blood supply chain from various perspectives, including how to manage uncertainty conditions, network features, decision variables, the type of objective function, and solution methods. This section briefly reviews noteworthy works addressing these issues.

2.1 | Uncertainty Approach

Most researchers have utilized fuzzy programming and robust optimization methods to manage uncertainty. Nahofti Kohneh and Teimoury [14] aimed to design a blood supply chain that effectively meets the blood unit recipients' needs during earthquake crises. Tehran was chosen as a case study to apply the problem to the real world, utilizing data from the city's blood transportation network. The problem was modeled using fuzzy programming. Zahiri er al. [15] presented a mixed integer linear programming model for strategic and tactical decision-making in a multi-period blood collection system. The authors applied a robust probabilistic programming approach to handle the uncertainty associated with model parameters. The application of this model was demonstrated through a real case study conducted in Iran. Zahiri and Pishvaee [16] proposed the design of a BSCN considering blood group compatibility. They have developed a multi-objective mathematical model to minimize the overall costs. Due to the inherent uncertainty in some input parameters, they have employed a credit-based robust programming model. Zhang and Jiang [17] presented a second-degree cone mixed-integer programming model with two objectives for emergency medical services. The model was formulated under uncertainty to balance the objectives, namely costs and responsiveness. To address uncertainty in the problem, they developed a robust optimization planning model. Momenitabar et al. [18] focused on strategic and tactical decision-making for a Closed-Loop Blood Supply Chain Network (CLBSCN). The study considered factors such as blood group compatibility and blood product storage life, aiming to optimize the network structure while incorporating lateral transshipment and maximizing service levels. Key parameters, including supply and demand, were modeled as fuzzy numbers to account for real-world uncertainty. The study proposed a fuzzy multi-objective Mixed-Integer Non-Linear Programming (MINLP) model to minimize total network costs and maximize the minimum service level to patients at each hospital.

2.2 | Decision Variables

From the perspective of features and decision variables in supply chain design, researchers have primarily focused on the location of fixed and temporary facilities, product transportation, and inventory management. Yaghoubi et al. [19] considering uncertainty in both blood supply and demand, a multi-objective mathematical model was developed for locating various facilities in the blood supply chain. The model takes into account necessary credits among facilities at different levels. Emadi and Pasek [20] proposed a two-stage location-allocation model for the BSCN, aiming to optimize blood inventory levels by minimizing total related costs. Various factors were considered constraints, such as ordering policies, lateral transshipment between hospitals, emergency orders from blood centers, limited capacity for each center, and the blood aging process. Hosseinifard and Abbasi [21] examined the importance of inventory centralization at the second echelon of a two-echelon supply chain dealing with perishable items. Replenishment at the first echelon was considered to be stochastic. The results demonstrated that the centralization of hospitals' inventory was a critical factor in the blood supply chain, enhancing its sustainability and resilience. Ghahremani-Nahr et al. [22] designed a BSCN to minimize the total cost, including demand and transportation costs. The network levels modeled

encompassed blood donation clusters, permanent and temporary blood transfusion centers, major laboratory centers, and blood supply points. The study aimed to determine these facilities' optimal number and location, allocate goods optimally between selected facilities, and identify the best transport routes for distributing goods to customer areas under uncertain conditions. Khojasteh Eghbali et al. [23] introduced a multi-objective mathematical model designed to create an efficient blood supply chain during disasters. The model considered temporary and fixed facilities necessary and explored potential blood facilities and route disruptions. Recognizing that disaster response operations involve uncertainties, the study presented an extended Interval-Valued Fuzzy (IVF) solution method based on the weighted multi-choice goal programming approach. Karadağ et al. [24] introduced a multi-objective mixed-integer locational-allocation model for the blood supply chain design problem, considering both mobile and permanent units in a supply chain network. The multi-objective structure of the model focused on minimizing distances between blood supply chain elements and the lengths of mobile unit routes. Dehaghani et al. [25] focused on a location-allocation problem within the BSCN, incorporating the M/M/m/k queue model. The proposed approach optimized the location and allocation of resources in the blood supply chain to enhance efficiency and minimize costs and waiting times, considering the specific characteristics of the blood donation process.

2.3 | Objective Function

From the problem's objective function perspective, researchers have focused on minimizing network costs, transportation costs, transportation time, and distances between facilities and developed a robust design model for a multi-period, single-product blood supply chain, considering uncertainty in demand parameters, aiming to ensure blood supply during crises [26]. The proposed model seeks to minimize the total costs of the blood supply chain, including the costs of locating fixed facilities, relocating mobile facilities, blood operational costs, transportation costs, and inventory holding costs. Hemmelmayr et al. [27] utilized integer programming models to make decisions regarding selecting hospitals that need to be covered daily by blood transport vehicles from blood donation centers. They also considered the uncertainty in demand and determined the required amount of blood for each hospital daily.

Haeri et al. [28] provided a multi-objective, integrated, resilient-efficient model for designing a BSCN under uncertainty. Various resiliency measures were introduced as optimization tools to enhance supply chain resilience and integrated into the network. The results indicate that simultaneously considering efficiency, resilience, and cost measures can improve BSCN design. Moreover, a trade-off among these three measures can be established based on decision-maker preferences.

Hosseini et al. [29] provided a BSCN design problem that optimized the costs of blood shortage and substitution, along with other common objective functions. The study proposed a MIP model to formulate the problem. Khalilpourazari and Hashemi Doulabi [4] presented a novel multi-objective Transportation-Location-Inventory-Routing (TLIR) formulation for the BSCN design problem, particularly in emergencies such as natural disasters and pandemics. The model aims to minimize total costs and transportation time, considering factors such as blood storage life, transportation modes, and the impact of earthquakes on facilities.

In contrast to previous studies, socio-economic factors and the impact of COVID-19 were incorporated into the BSCN design. A more efficient approach is a closed-loop network design, which aims for more economical and environmental benefits than a traditional design. Addressing this concern, Mousavi et al. [30] presented a bi-objective and sustainable BSCN, considering both social and environmental factors related to blood decomposition.

The problem incorporated aspects of uncertainty, considering the amount of blood gathered from blood transfusion centers and the decomposition ratio in the blood decomposition center. Tirkolaee et al. [3] aimed to optimally configure a multi-echelon BSCN under uncertainties in demand, capacity, and blood disposal rates. The supply chain included blood donors, collection facilities, blood banks, regional hospitals, and consumption points. A novel bi-objective Mixed-Integer Linear Programming (MLP) model was proposed

to formulate the problem, with the goals of minimizing network costs and maximizing job opportunities, all while considering the adverse effects of the pandemic. Interactive possibilistic programming was then employed to optimally address the problem given the unique conditions of the pandemic.

2.4 | Solution Method

Finally, from the point of view of solution methods for the multi-objective formulation, both exact solution approaches such as epsilon-constraint and goal programming, as well as approximation approaches such as Genetic Algorithm (GA), Differential Evolution (DE) and Particle Swarm Optimization (PSO) have been more widely used by researchers. Kohneh et al. [31] designed a blood product supply chain aligned with real-world conditions to meet the demand for these products during earthquake crises. Due to the affected city's inability to supply the required blood products during the crisis, transferring these products from centers in neighboring provinces has become necessary. This issue has been modeled as a bi-objective problem under fuzzy uncertainty, and an epsilon-constraint method has been used to solve it. Mohammadian-Behbahani et al. [32] presented a non-deterministic multi-objective optimization model for designing a BSCN, focusing on facility location and allocation in the event of disruptions.

The proposed model is ultimately solved using data from Tehran city and previous studies in the field of blood transportation supply chains, employing the epsilon-constraint method and a robust optimization approach. Farrokhizadeh et al. [33] proposed a location-allocation model. They argued that considering the significant variations in blood donor visits and hospital demands across different seasons and months, it is unrealistic to treat parameters as deterministic. Therefore, they considered certain sensitive and influential parameters, such as supply and demand, uncertain.

To cope with this uncertainty, they employed a robust programming approach. Eshghi et al. [34] proposed a novel two-objective model for the location-allocation of components in the BSCN under uncertainty. The objectives of the model are to minimize the network's total cost and transportation time within the network. Due to the inherent uncertainty in BSCNs, some parameters, such as transportation time, demand, and cost, are considered fuzzy. The proposed model has been solved using the epsilon-constraint method in various dimensions.

Eskandari-Khanghahi et al. [35] formulated a possibilistic optimization model for a multi-period, multi-objective, sustainable blood supply chain, considering uncertain data due to unpredictable conditions during and after a disaster. The objectives involved minimizing total costs and environmental impacts while maximizing social effects to enhance network efficiency. The ε-constraint method was employed to transform the multi-objective mathematical model into a single-objective one. Rajendran and Ravi Ravindran [36] introduced a stochastic integer programming model under demand uncertainty to determine ordering policies across the blood supply chain. A GA variant, Modified Stochastic Genetic Algorithm (MSGA), was proposed for large-sized problems. Based on the results, hospitals and blood centers can select the most suitable ordering policy for their specific demand and cost settings.

Fallahi et al. [37] formulated a closed-loop supply chain of blood products considering blood transportation equipment and the relevant quality features. Then, a DE algorithm, enhanced by extending two new versions of DE, was employed to solve the problem. The hub location approach introduced a new BSCN for disaster scenarios [38]. A new MIP model based on hub location was presented for intercity transportation. Given the complexity of this problem, two new methods were developed based on PSO and DE algorithms to solve practical-sized problems. Arani et al. [39] discussed the dynamic subject of blood banking and distribution, considering the lateral resupply of blood products.

The proposed mixed-integer mathematical programming model included three objectives related to sustainability concepts. A scenario-based optimization approach and a revised multi-choice goal programming technique were employed to address uncertainties and multi-objectiveness. The results confirmed that the virtue of lateral resupply improves the performance indicators of the BSCN. Haghjoo et al. [40] introduced a dynamic, robust location-allocation model for designing a BSCN considering facility disruption risks and

uncertainty in a disaster. The model adopted a scenario-based robust approach to address the inherent uncertainty, which includes significant periodic variations in demands and potential disruptions to facilities.

Hosseini-Motlagh et al. [41] represented the approach aimed at a simultaneous investigation into three interdependent challenges of the BSCN including 1) motivating donors, 2) optimizing location and capacity decisions, and 3) controlling the reliability and robustness of the network under combinatorial risk. Confirming the crucial role of blood donors in the BSC, the study incorporated motivational initiatives to encourage blood donations and maintain a sufficient blood supply.

Data Envelopment Analysis (DEA) was employed to evaluate the pool of location alternatives for establishing facilities and assess efficiency. A mixed-integer programming model was proposed to support simultaneous location and capacity decisions. *Table 1* presents an overview of studies which integrate different aspects in blood supply change network design.

Based on the aforementioned works, the present research proposes a MIP model for strategic and tactical decision-making in blood collection systems. The objective is to optimize the number and location of blood banks and fixed and temporary facilities, considering various components of the BSCN, including donor groups, fixed facilities, temporary facilities, blood banks, and procurement and processing centers.

The study addresses the challenge of blood storage and the need to manage blood systems effectively. The proposed model incorporates uncertainty in parameters, and an interactive fuzzy solution approach based on the extended credibility measure is developed for solving the fuzzy optimization model.

3 | Mathematical Model

The assumptions we have considered in constructing the mathematical model are as follows:

I. Our facilities include fixed, temporary, and blood banks.

II. The main parameters of the proposed model include demand for fixed facilities, blood banks, the distance between donor groups and fixed facilities, the distance between donor groups and temporary facilities, and the cost of placing fixed and temporary facilities.

III. The parameters have been considered as uncertain.

IV. The facilities in different layers have limited capacity.

V. Blood is divided into 6 blood products.

VI. It is possible to export and import blood products, taking into account their storage duration.

VII. A 7-year planning horizon has been considered.

To describe the proposed BSCN, we first need to explain it (*Fig. 1*) and then provide a breakdown of its layers. This network comprises blood donor groups, temporary facilities (blood collection vans and buses), main facilities (hospitals), a blood bank, blood preparation and processing centers, and external customers. After blood donation, donor groups may send the blood to fixed or temporary facilities. Temporary facilities allocate a portion of the blood to fixed facilities and the blood bank. Fixed facilities directly send the blood to the blood bank. The blood entering the blood bank must undergo testing, analysis, storage, and distribution. To extend the storage life of the blood, it needs to be sent to blood preparation and processing centers, divided into six blood products.

These products include whole blood with a maximum storage duration of 35 days, packed red blood cells with a maximum storage duration of 42 days, washed red blood cells with a storage duration of 24 hours, frozen red blood cells with a maximum storage duration of 14 days, platelets with a storage duration of 5 days, and fresh frozen plasma, which can be stored for one year using the apheresis method (separation of blood components and subsequent return). Additionally, based on the blood quantity (shortage or surplus), we may receive blood from external customers (import of blood products) or send blood to them (export of blood products).

Table 1. Summarized literature review.

Article	Period		Parameters		Objective Function				Constraints				Uncertainty			Programming	
	Single	Multiple	Deterministic	Stochastic	Profit/ Cost	Location/ Allocation	Service Level	Resilience	Blood Demand	Blood Storage	Blood Transmission	Capacity	Stochastic	Fuzzy	Robust	Linear	Non-Linear
[14]	√			√	√						√			√		√	
[15]		√		√	√				√						√	√	
[16]	√			√	√				√						√	√	
[17]		√		√	√				√						√	√	
[18]	√			√			√			√				√			√
[19]		√		√		√			√				√			√	
[20]	√		√			√						√				√	
[21]		√		√				√					√			√	
[22]		√		√	√	√			√		√		√			√	
[23]		√		√		√			√		√			√		√	
[24]	√		√		√						√					√	
[25]	√		√		√	√					√					√	
[26]		√		√	√				√		√				√	√	
[27]	√			√		√					√		√			√	
[28]	√			√	√			√			√		√			√	
[29]	√		√		√					√						√	
[30]		√		√	√						√		√			√	
[31]		√		√	√				√		√			√		√	
[32]		√		√		√			√		√				√	√	
[33]		√		√		√			√						√	√	
[34]		√		√	√	√					√			√		√	
[35]		√		√	√				√				√			√	
[36]	√			√	√				√				√			√	
[37]		√	√		√						√					√	
[38]		√	√		√	√					√					√	
[39]		√	√		√				√								√
[40]		√		√		√			√						√	√	
[41]		√		√		√						√			√	√	
This study		√		√	√	√			√	√	√	√		√		√	

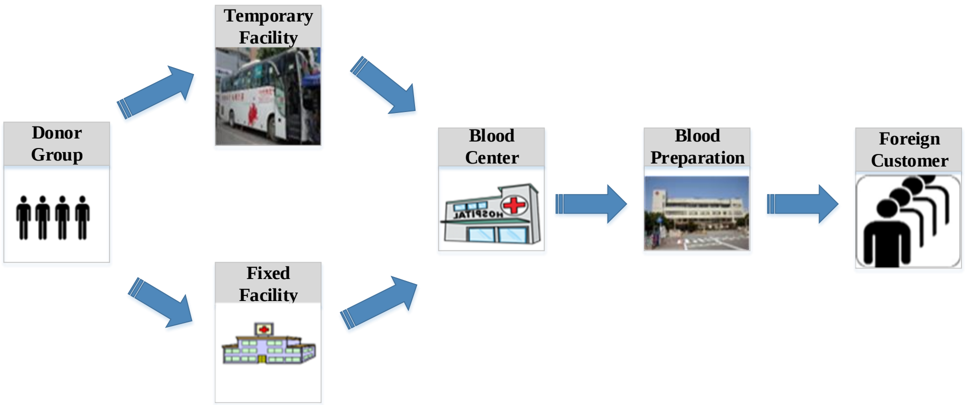

Fig. 1. Blood supply chain network.

3.1 | Model Notation

The indices, parameters, and variables used in the proposed mathematical modeling of the problem are described as follows.

Indices

I	Index for the set of blood donor groups (i = 1,…,I).
J	Index for the set of candidate locations for temporary facilities (j = 1,…,J).
K	Index for the set of candidate locations for fixed facilities (k = 1,…,K).
W	Index for the set of blood bank centers (w = 1,…,W).
P	Index for the set of blood products (p = 1,…,P).
T	Index for the set of time periods (t = 1,...,T).

Parameters

FC_{kt}	Fixed cost of placing a fixed facility at candidate location k in time period t ($/month).
TC_{kwt}	Cost of transferring blood from candidate fixed location k to blood bank w in time period t ($/kg.km.month).
DC_{jkt}	Cost of delivering blood from temporary facility at candidate location j to fixed facility at candidate location k in time period t ($/kg.km.month).
TC_{jwt}	Cost of transferring blood from temporary facility at candidate location j to blood bank w in time period t ($/kg.km.month).
HC_w	Cost of holding blood in blood bank w ($/kg).
DF_{kt}	Blood demand at fixed facility in candidate location k in time period t (kg/month).
R_{ij}	Distance between blood donor group i and temporary facility at candidate location j (km).
rf_{ik}	Distance between blood donor group i and fixed facility at candidate location k (km).
r_o	Maximum coverage distance for temporary facilities (if r_{rij ≤ ro, group i can be covered by facility j) (km).
rl_o	Maximum coverage distance for fixed facilities (if rlik ≤ rlo, group i can be covered by facility k) (km).
C_{jt}	Capacity of temporary facility at candidate location j in time period t (kg/month).
C_{kt}	Capacity of fixed facility at candidate location k in time period t (kg/month).

G_{it}	Capacity of blood donor group i in time period t (kg/month).
M	A very large number.
FCT_{jt}	Fixed cost of placing a temporary facility at candidate location j in time period t ($/month).
FCC_{wt}	Fixed cost of placing a blood bank at location w in time period t ($/month).
PC_{pwt}	Cost of producing blood product p at blood bank w in time period t ($/kg.month).
$D2_{pwt}$	Demand for blood product p at blood bank w in time period t (kg/month).
AC_{ijt}	Cost of allocating blood donor group i to temporary facility at candidate location j in time period t ($/kg.km.month).
ACT_{ikt}	Cost of allocating blood donor group i to fixed facility at candidate location k in time period t ($/kg.km.month).
ExB_{pt}	Revenue from exporting blood product p in time period t ($/kg.month).
Ca_{pwt}	Capacity of blood product p at blood bank w in time period t (kg/month).
α_p	Conversion coefficient for blood product p.
ImC_{pt}	Cost incurred from importing blood product p in time period t ($/kg.month).

Decision variables

$Im1_{kt}$	Import of blood to fixed facilities at candidate location k in time period t ($/km.month).
V_{ikt}	Volume of blood from donor groups i in fixed facilities at candidate location k in time period t (kg/km.month).
$V1_{jkt}$	Volume of blood in temporary facilities at candidate location j in fixed facilities at candidate location k in time period t (kg/km.month).
$V2_{ijt}$	Volume of blood from donor groups i in temporary facilities at candidate location j in time period t (kg/km.month).
q_{ijt}	If donor groups i are allocated to temporary facilities at candidate location j in time period t, then 1; otherwise, 0.
$q1_{ikt}$	If donor groups i are allocated to fixed facilities at candidate location k in time period t, then 1; otherwise, 0.
x_k	If fixed facilities at candidate location k are established, then 1; otherwise, 0.
xt_{jt}	If temporary facilities at candidate location j are established in time period t, then 1; otherwise, 0.
Ex_{pwt}	Export of blood product p from blood bank w in time period t (kg/month).
$I2_{pwt}$	Inventory level of blood product p in blood bank w in time period t (kg/month).
U_{jwt}	Amount of blood collected from temporary facilities at candidate location j to blood bank w in time period t (kg/km.month).
Y_{kwt}	Amount of blood collected from fixed facilities at candidate location k to blood bank w in time period t (kg/km.month).
$X2_W$	If blood bank is established in w, then 1; otherwise, 0.

BP_{pwt}	Amount of blood product p in blood bank w in time period t (kg/month).
Im_{pwt}	Import of blood product p to blood bank w in time period t (kg/month).
$I1_{kt}$	Inventory level of fixed facilities at candidate location k in time period t (kg/month).
$\lambda_{kt}.\gamma_{ik}.\beta.$ $\delta_{it}.\omega_{jt}.$ $\varphi ij.\Phi.\chi_{jt}.$ $\theta_{k}.\tau_{pwt}$	Minimum acceptable levels of confidence for constraints.

3.2 | Model Formulation

In many real-life situations, the input parameters of the supply chain network exhibit a high degree of uncertainty. A probabilistic constraint-based programming approach was used to model the problem. This method is an efficient computational fuzzy mathematical programming technique that relies on various types of fuzzy numbers, such as triangular and trapezoidal shapes. It enables the decision-maker to consider certain probabilistic constraints at minimum acceptable confidence levels. Until now, many researchers have utilized the concept of fuzziness to account for uncertainty. This article also used a trapezoidal distribution function for fuzzy parameters. The problem has been modeled using the following two equations:

$$Cr\{\acute{\varepsilon} \le r\} \ge \alpha \leftrightarrow r \ge (2-2\alpha)\,\acute{\varepsilon}(3) + (2\alpha-1)\,\acute{\varepsilon}(4). \tag{1}$$

$$Cr\{\acute{\varepsilon} \ge r\} \ge \alpha \leftrightarrow r \le (2-2\alpha)\acute{\varepsilon}(1) + (2\alpha-1)\acute{\varepsilon}(2). \tag{2}$$

The above equations can be directly transformed into their equivalent when a critical value, alpha, is proposed to convert the fuzzy probability constraint into its equivalent form. In this study, trapezoidal fuzzy independent numbers were used to deal with the uncertainty of parameters. The problem modeling is as follows:

$$\begin{aligned}
\text{MinE}\,[Z] = {} & \textstyle\sum_{j.t}\left(\frac{FCT_{jt(1)}+FCT_{jt(2)}+FCT_{jt(3)}+FCT_{jt(4)}}{4}\right)x_{jt} + \sum_{k.t}\left(\frac{FC_{kt(1)}+FC_{kt(2)}+FC_{kt(3)}+FC_{kt(4)}}{4}\right)x_{k} + \\
& \textstyle\sum_{j.k.t}\left(\frac{DC_{jkt(1)}+DC_{jkt(2)}+DC_{jkt(3)}+DC_{jkt(4)}}{4}\right)V1_{jkt} + \\
& \textstyle\sum_{j.w.t}\left(\frac{TCT_{jwt(1)}+TCT_{jwt(2)}+TCT_{jwt(3)}+TCT_{jwt(4)}}{4}\right)U_{jwt} + \\
& \textstyle\sum_{k.w.t}\left(\frac{TC_{kwt(1)}+TC_{kwt(2)}+TC_{kwt(3)}+TC_{kwt(4)}}{4}\right)Y_{kwt} + \sum_{w.t}\left(\frac{HC_{w(1)}+HC_{w(2)}+HC_{w(3)}+HC_{w(4)}}{4}\right)I_{pwt} + \\
& \textstyle\sum_{p.w.t}\left(\frac{PC_{pwt(1)}+PC_{pwt(2)}+PC_{pwt(3)}+PC_{pwt(4)}}{4}\right)BP_{pwt} + \\
& \textstyle\sum_{w.t}\left(\frac{FCC_{wt(1)}+FCC_{wt(2)}+FCC_{wt(3)}+FCC_{wt(4)}}{4}\right)x2_{w} + \\
& \textstyle\sum_{i.j.t}\left(\frac{AC_{ijt(1)}+AC_{ijt(2)}+AC_{ijt(3)}+AC_{ijt(4)}}{4}\right)\left(\frac{r_{ij(1)}+r_{ij(2)}+r_{ij(3)}+r_{ij(4)}}{4}\right)q_{ijt} + \\
& \textstyle\sum_{i.k.t}\left(\frac{ACF_{ikt(1)}+ACF_{ikt(2)}+ACF_{ikt(3)}+ACF_{ikt(4)}}{4}\right)\left(\frac{rf_{ik(1)}+rf_{ik(2)}+rf_{ik(3)}+rf_{ik(4)}}{4}\right)q1_{ikt} + \\
& \textstyle\sum_{p.w.t}\left(\frac{ImC_{pt(1)}+ImC_{pt(2)}+ImC_{pt(3)}+ImC_{pt(4)}}{4}\right)Im_{pwt} - \\
& \textstyle\sum_{p.w.t}\left(\frac{ExB_{pt(1)}+ExB_{pt(2)}+ExB_{pt(3)}+ExB_{pt(4)}}{4}\right)Ex_{pwt}.
\end{aligned} \tag{3}$$

$$I2pw, t-1 + BP_{pwt} - I2_{pwt} - Ex_{pwt} = D2_{pwt}, \quad \text{for all } p.w.t. \tag{4}$$

$$I1_{k.t-1} + I1_{k.t-1}\sum_{j} V1_{jkt} + \sum_{i} V_{ikt} - I1_{kt} - \sum_{w} Y_{kwt} = D1_{kt}, \quad \text{for all } k.t. \tag{5}$$

$$\sum_{j} V1_{jkt} + \sum_{i} V_{ikt} \le x_{k}\left[(2\lambda_{kt}-1)Cm_{kt(1)} + (2-2\lambda_{kt})Cm_{kt(2)}\right], \quad \text{for all } k.t. \tag{6}$$

$$\sum_k V_{ikt} + \sum_j V2_{ijt} \le (2\delta_{it} - 1)g_{it(1)} + (2 - 2\delta_{it})g_{it(2)}, \quad \text{for all i. t.} \tag{7}$$

$$\sum_i V2_{ijt} \le x1_{jt}\left[(2\omega_{jt} - 1)Ct_{jt(1)} + (2 - 2\omega_{jt})Ct_{jt(2)}\right], \quad \text{for all i. t.} \tag{8}$$

$$\sum_i V2_{ijt} = \sum_k V1_{jkt} + \sum_w U_{jwt}, \quad \text{for all j. t.} \tag{9}$$

$$ro \ge qijt\,[(2 - 2\varphi ij)rij(3) + (2\,\varphi ij - 1)rij(4)], \quad \text{for all i. j. t.} \tag{10}$$

$$r1_O \ge q1_{ikt}\left[(2 - 2\gamma_{ik})rf_{ik(3)} + (2\,\gamma_{ik} - 1)rf_{ik(4)}\right], \quad \text{for all i. k. t} \tag{11}$$

$$U_{jwt} \le q_{ijt}\left[(2\beta - 1)M_{(1)} + (2 - 2\beta)M_{(2)}\right], \quad \text{for all i. j. w. t.} \tag{12}$$

$$Y_{kwt} \le q1_{ikt}\left[(2\Phi - 1)M_{(1)} + (2 - 2\Phi)M_{(2)}\right], \quad \text{for all i. k. w. t.} \tag{13}$$

$$q_{ijt} \le (2\chi_{jt} - 1)xt_{jt(1)} + (2 - 2\chi_{jt})xt_{jt(2)}, \quad \text{for all i. j. t.} \tag{14}$$

$$q1_{ikt} \le (2\theta_k - 1)x_{k(1)} + (2 - 2\theta_k)x_{k(2)}, \quad \text{for all i. k. t.} \tag{15}$$

$$\sum_j \alpha_p U_{jwt} + \sum_k \alpha_p Y_{kwt} \le x2_w\left[(2\tau_{pwt} - 1)Ca_{pwt(1)} + (2 - 2\tau_{pwt})Ca_{pwt(2)}\right], \quad \text{for all p. w. t.} \tag{16}$$

$$\sum_j \alpha_p U_{jwt} + \sum_k \alpha_p Y_{kwt} = BP_{pwt}, \quad \text{for all p. w. t.} \tag{17}$$

$$q_{ijt} \in \{o. 1\}, \quad \text{for all i. j. t.} \tag{18}$$

$$q1_{ikt} \in \{0.1\}, \quad \text{for all i. k. t.} \tag{19}$$

$$x_k \in \{0.1\}, \quad \text{for all k.} \tag{20}$$

$$xt_{jt} \in \{0.1\}, \quad \text{for all j. t.} \tag{21}$$

$$x2_w \in \{0.1\}, \quad \text{for all w.} \tag{22}$$

$$\lambda_{kt}\gamma_{ik}.\ \beta.\ \delta_{it}.\ \omega_{jt}.\ \varphi ij.\ \Phi.\ \chi_{jt}.\ \theta_k.\ \tau_{pwt} > 0.5. \tag{23}$$

All variables are positive. (24)

Eq. (3) minimizes the following costs: 1) fixed facility setup costs, temporary facility costs, and blood bank costs, 2) maintenance costs of blood products, 3) allocation costs of donor groups to temporary and fixed facilities, considering the distance of each, 4) import costs of blood products, 5) production costs of blood products, 6) blood transfer costs from temporary and fixed facilities to the blood bank, and 7) blood delivery costs from temporary facilities to fixed facilities, minus the income from the export of blood products.

Eq. (4) states that the demand for blood products is met by the sum of the inventories of the previous periods and the amount of blood products minus the export of blood products and the current period's inventory. *Eq. (5)* describes how blood demand is met at fixed facilities. It is defined as the blood inventory at fixed facilities plus the volume of blood collected from temporary facilities to the blood bank minus the volume collected by fixed facilities from donors and the amount of blood supplied to the blood bank. *Eq. (6)* represents the maximum capacity of fixed facilities. *Eq. (7)* ensures that donor groups can only donate a specific blood volume. *Eq. (8)* represents the capacity constraint for temporary blood centers. *Eq. (9)* states that the total volume of blood collected by temporary facilities from donors in each period equals the blood delivered from temporary facilities to fixed facilities and blood banks.

Eq. (10) ensures that donors within a distance of "ro" from temporary facilities assigned to them are covered. *Eq. (11)* ensures that donors within a distance of "r1o" from fixed facilities assigned to them are covered. *Eq.*

(12) states that the blood donated by a donor cannot be sent to a temporary facility that is not assigned to that donor. *Eq. (13)* indicates that the blood donated by a donor cannot be sent to a fixed facility that is not assigned to that donor. *Eqs. (14)* and *(15)* state that temporary and fixed facilities cannot go to a location where no facility exists. *Eq. (16)* represents the constraint on blood flow in blood centers. *Eq. (17)* states that the produced amount of blood products equals the amount of blood transferred from temporary facilities to the blood bank and from fixed facilities to the blood bank. *Eqs. (18)-(22)* define the domain of decision variables as binary ones. *Eq. (23)* assumes that probabilistic constraints should have confidence levels greater than 0.5.

3.3 | Model Analysis

Statistics from the last few decades indicate that unforeseen disasters such as floods and earthquakes have been the main cause of many deaths. Iran is also considered one of the earthquake-prone areas. One of the concerns after earthquakes is ensuring a timely and sufficient blood supply for the injured. Additionally, the need for effective blood supply chain management is underscored by the existence of uncontrollable diseases such as thalassemia, hemophilia, and cancer. To assess and evaluate the proposed model, we focused on a case study of Urmia city. The required data were estimated based on the population and the number of hospitals in Urmia. As mentioned before, the demand was estimated based on the population of the case study. The cost of constructing permanent facilities is significantly higher than that of temporary facilities.

On the other hand, the location of fixed facilities remains unchanged throughout the 7-year planning horizon, but temporary facilities can be changed. The capacity of fixed facilities is greater than that of temporary facilities. The values of the fixed costs for placing a blood bank at candidate locations and blood demands at fixed facilities in candidate locations in each time period are shown in *Tables 2* and *3* as fuzzy numbers. It should be noted that all numerical tables are the outcomes of our calculations in the case study.

Table 2. Fixed cost of placing a blood bank at location w in time period t.

w \ t	1	2	3	4	5	6	7
1	173000,174000, 175000,176000	200205,201205, 202205,203205	222500,223500, 224500,225500	250750,251750, 252750,253750	280000,281000, 282000,283000	301250,302250, 303250,304250	330500,331500, 332500,333500

Table 3. Blood demand at fixed facility in candidate location k in time period t.

k \ t	1	2	3	4	5	6	7
1	2370000,2371000, 2372000,2373000	2742000,2743000, 2744000,2745000	2714000,2715000, 2716000,2717000	2792000,2793000, 2794000,2795000	2493000,2494000, 2495000,2496000	2784000,2785000, 2786000,2787000	2616000,2617000, 2618000,2619000
2	2350000,2351000, 2352000,2353000	2724000,2725000, 2726000,2727000	2720000,2721000, 2722000,2723000	2790000,2791000, 2792000,2793000	2501000,2502000, 2503000,2504000	2782000,2783000, 2784000,2785000	270000,2701000, 2702000,2703000
3	2420000,2421000, 2422000,2423000	2805000,2806000, 2806000,2807000	2785000,2786000, 2787000,2788000	2832000,2833000, 2834000,2835000	2695000,2696000, 2697000,2698000	2825000,2826000, 2827000,2828000	2794000,2795000, 2796000,2797000
4	2470000,2471000, 2472000,2473000	2864000,2865000, 2866000,2867000	2852000,2853000, 2854000,285000	2895000,2896000, 2897000,2898000	2700000,2701000, 2702000,2703000	2886000,2887000, 2888000,2889000	2865000,2866000, 2867000,2868000
5	2320000,2321000, 2322000,2323000	2691000,2692000, 2693000,2694000	2674000,2675000, 2676000,2677000	2696000,2697000, 2698000,2699000	2586000,2587000, 2588000,2589000	2690000,2691000, 2692000,2693000	2656000,2657000, 2658000,2659000
6	2450000,2451000, 2452000,2453000	2842000,2843000, 2844000,2845000	2824000,2825000, 2826000,2827000	2855000,2856000, 2857000,2858000	2762000,2763000, 2764000,2765000	2853000,2854000, 2855000,2856000	2835000,2836000, 2837000,2838000
7	2440000,2441000, 2442000,2443000	2830000,2831000, 2832000,2833000	2804000,2805000, 2806000,2807000	2846000,2847000, 2848000,2849000	2785000,2786000, 2787000,2788000	2834000,2835000, 2836000,2837000	2805000,2806000, 2807000,2808000

Urmia city has a population of approximately 667,000, and its blood demand is met through blood collection in fixed locations (i.e., hospitals) and temporary facilities (i.e., blood collection buses). The number of donor groups was considered to be 22, taking into account the urban areas of Urmia. There are 7 hospitals and 10 temporary facilities in this city. After collecting the data, the results were obtained using GAMS software version 23.5 with the CPLEX solver, which is discussed below.

Table 4. The imported amount of blood product p to blood bank w in time period t.

p	w	t 1	2	3	4	5	6	7
1	1	435670	534789	500099	421780	429980	479076	490664
2	1	335800	340115	329743	390412	300689	384221	378500
3	1	99750	67890	94032	0	55400	76590	0
4	1	59623	57865	64220	77005	45600	50400	0
5	1	0	0	0	0	0	0	0
6	1	283789	298600	265400	275590	257990	289532	200721

Considering the categorization of blood products into six groups based on their storage life and the varying demand for each product, determining the optimal amount and duration for storing blood is one of the influential factors in a designed blood supply chain. The result obtained from *Table 4* indicates that the inventory of blood products has been determined based on their storage life. In other words, having a lower quantity of blood products with a shorter storage life in the blood bank is preferable. The amount of blood from donor groups sent to fixed facilities is significantly higher than that of temporary facilities. This result is logical because these facilities have a larger capacity.

Table 5. Amount of blood product p in blood bank w in time period t.

p	w	t 1	2	3	4	5	6	7
1	1	270000	127000	147000	180000	225000	151000	165000
2	1	115000	265000	215000	160000	200000	200000	119000
3	1	116000	117000	119000	131000	122000	125000	121000
4	1	120000	118000	125000	119000	117000	116000	128000
5	1	200000	220000	195000	210000	175000	205000	180000
6	1	225000	150000	175000	155000	205000	160000	270000

Table 5 shows that the production of the third and fourth blood products does not vary significantly over time and are very close to each other at different time periods. However, the production of other blood products has many fluctuations. The fluctuations in blood products over different periods have been determined based on their storage life, demand levels, and the capacity of available facilities and blood banks. Therefore, when designing the blood supply chain, planning for blood products with higher fluctuations will be prioritized. To this end, appropriate decisions must be made to maintain inventory levels for these blood products.

Considering the necessity for reducing costs in designing the blood supply chain, the problem was modeled to minimize all blood supply chain costs, including the cost of setting up fixed and temporary facilities, the cost of storing blood units, the cost of allocating blood donor groups to facilities, production costs, transportation costs, and the cost of importing blood products. In other words, the location and number of blood supply chain entities and the amount of blood product transportation between these entities were determined so that the total supply chain cost is minimized while satisfying the extant constraints.

3.4 | Sensitivity Analysis

To investigate the sensitivity of the optimal results, a series of sensitivity analyses on the main parameters of the problem was executed. *Figs. 2-7*, different parameters are analyzed from 20% down to 20% up, specified as 0.8 to 1.2 in the respective figures.

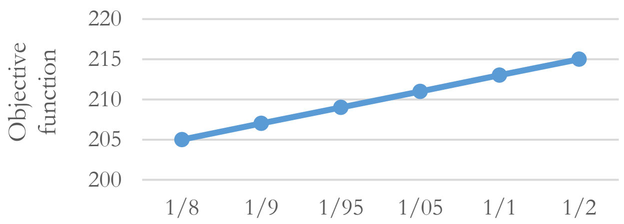

Fig. 2. Fixed facility costs.

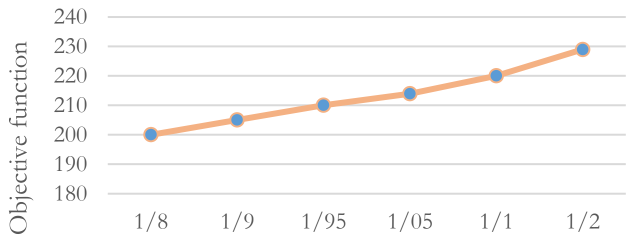

Fig. 3. Transmission costs from fixed facilities to blood banks.

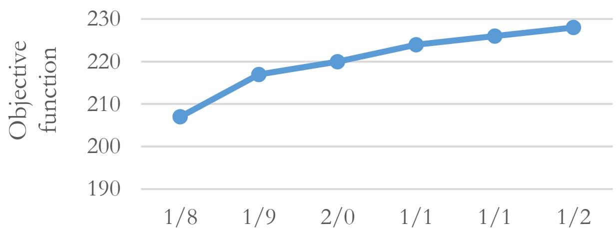

Fig. 4. Delivery costs from temporary to fixed facilities.

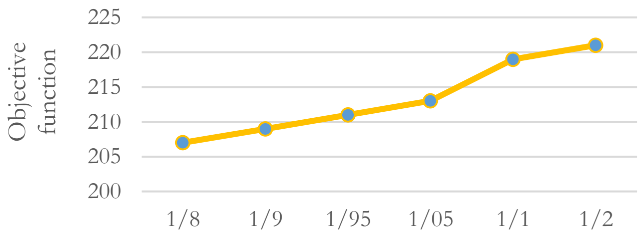

Fig. 5. The cost of production of blood products in the blood bank.

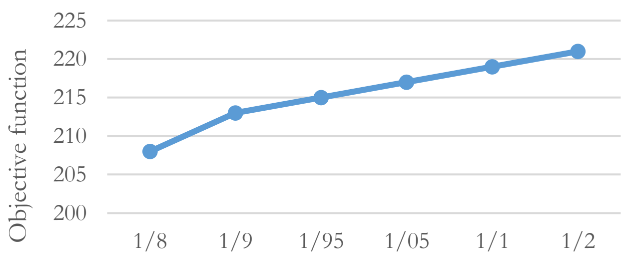

Fig. 6. The demand for blood products in the blood bank.

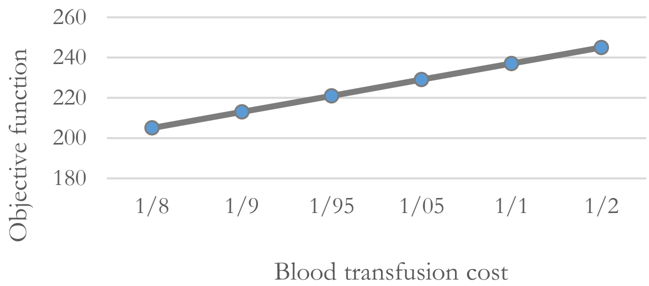

Fig. 7. The cost of blood transfusion from the temporary facility to the blood bank.

Figs. 2 and *7* show that increasing or decreasing the fixed facility costs and the transfer cost from temporary facilities to the blood bank have an equal impact on the objective function and affect it with the same ratio. Considering the same effects of increasing and decreasing these parameters on the value of the objective function, it can be said that the value of the objective function of the problem is not greatly affected by the numerical values of these parameters. Therefore, the estimate close to the actual values is sufficient.

As can be seen in *Figs. 3* and *5*, which demonstrate the sensitivity analysis of the blood transfer cost from fixed facilities to the blood bank and the cost of blood products in the blood bank, the slope of the drawn line is more sensitive in the ranges of a 10% increase to a 20% increase and a 5% increase to a 10% increase respectively compared to other points. In other words, increasing these parameters has a greater impact on the objective function of the problem. Therefore, overestimating these parameters can significantly change the model results and reduce validity. Hence, it is necessary to consider an appropriate upper bound for them.

Finally, *Figs. 4* and *6* demonstrate that decreasing delivery costs from temporary to fixed facilities and the demand for blood products has a steeper slope than increasing these parameters. In other words, decreasing these parameters has a greater impact on the objective function of the problem. Thus, underestimating these parameters can lead to significant changes in the model results and affect the stability of the model outputs. In this regard, it is necessary to consider an appropriate lower bound for them.

In summary, based on the sensitivity analysis conducted, it can be concluded that poor estimation of the main parameters of the problem can reduce the validity of the results. Therefore, it is crucial to prioritize the model parameters and apply the utmost precision in estimating the values of the influential ones.

4 | Conclusion

The need for blood donors and their products and ensuring an adequate blood supply are challenges faced by healthcare systems. Furthermore, uncertainty is crucial in the blood supply chain, especially during crises like earthquakes and pandemics. Perishability, the short lifespan of blood components, and unpredictability in demand volumes make managing the blood supply chain more complex. In this regard, designing the BSCN under uncertainty is essential to meet fluctuating demand, address logistical challenges, respond to emergencies, and ensure the quality and safety of blood products throughout the supply chain.

This research aimed to present a comprehensive MIP model under uncertainty for strategic and tactical decision-making in the blood supply chain over a determined planning horizon, which has not been addressed much in previous studies. This model makes decisions regarding the optimal number and location of the blood supply network entities, including donor groups, fixed facilities such as hospitals, temporary facilities such as blood collection containers and mobile blood collection buses, blood banks, and processing centers. The fuzzy theory approach has been used to model the problem under conditions of uncertainty. An interactive fuzzy solution approach based on the extended credibility measure was developed to solve the fuzzy optimization model.

On the other hand, the perishability of blood is an important factor in the model for which we decomposed blood products into six groups to extend the blood storage duration. Additionally, it was possible to import

and export various blood products. It was implemented in a case study of Urmia, a city in Iran, to validate the proposed model and design its optimal BSCN.

The results obtained from designing and implementing the proposed model in a case study indicate the desirable efficiency of the model in determining the optimal number and location of facilities as well as the optimal amount of blood transfer between different entities of the blood supply chain in which while satisfying the extant constraints, the total supply chain cost was minimized. The categorization of blood products determined the optimal amount and duration for storing blood into six different groups based on their storage life and the varying demand for each product.

In the same direction, the model results confirmed the need to keep smaller amounts for products with a shorter storage life. In addition, it can be mentioned that the production of the third and fourth blood products does not vary significantly over time and is very close to each other at different time periods. However, the production of other blood products has many fluctuations. From the point of view of managerial insights, in designing the blood supply chain, planning for blood products with higher fluctuations will be prioritized. To this end, appropriate decisions must be made to maintain inventory levels for these blood products. Also, the number and location of facilities and the amount of blood transfer between different entities must be determined to minimize the overall cost of the BSCN. As another conclusion of the model, the amount of blood from donor groups to fixed facilities is significantly higher than the temporary facilities.

Based on the sensitivity analysis, it can be concluded that poor estimation (overestimation or underestimation) of the main parameters of the problem can reduce the validity of the results. Therefore, it is important to prioritize the model parameters and apply the utmost precision in estimating the values of the influential ones. The approach presented in this research is expandable from various aspects. Future research can consider transportation scheduling, optimal facility capacity determination, blood center location selection, and routing blood transportation from collection centers to transfer centers. Additionally, focusing on coping with shortages and responding to all demands considering the significant costs of shortages can be mentioned as a practical idea.

Author Contribution

Conceptualization, A.N., and R.B.; Methodology, R.B.; Validation, A.N.; formal analysis, A.N., and R.B.; investigation, A.N.; resources, A.N. and R.B.; data maintenance, R.B.; writing-creating the initial design, A.N. and R.B.; writing-reviewing and editing, A.N.; visualization, A.N.; monitoring, A.N., and R.B.; project management, A.N. and R.B.; All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Data Availability

Data presented in this study are available upon request from the corresponding author.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Ala, A., Simic, V., Bacanin, N., & Tirkolaee, E. B. (2024). Blood supply chain network design with lateral freight: a robust possibilistic optimization model. *Engineering applications of artificial intelligence*, *133*(1), 108053. DOI:10.1016/j.engappai.2024.108053

[2] Ben Elmir, W., Hemmak, A., & Senouci, B. (2023). Smart platform for data blood bank management: forecasting demand in blood supply chain using machine learning. *Information (Switzerland)*, *14*(1), 31. DOI:10.3390/info14010031

[3] Tirkolaee, E. B., Golpîra, H., Javanmardan, A., & Maihami, R. (2023). A socio-economic optimization model for blood supply chain network design during the COVID-19 pandemic: an interactive possibilistic programming approach for a real case study. *Socio-economic planning sciences*, *85*(1), 101439. DOI:10.1016/j.seps.2022.101439

[4] Khalilpourazari, S., & Hashemi Doulabi, H. (2023). A flexible robust model for blood supply chain network design problem. *Annals of operations research*, *328*(1), 701–726. DOI:10.1007/s10479-022-04673-9

[5] Beliën, J., & Forcé, H. (2012). Supply chain management of blood products: a literature review. *European journal of operational research*, *217*(1), 1–16. DOI:10.1016/j.ejor.2011.05.026

[6] Elelamy, A. F., Elgazery, N. S., & Ellahi, R. (2020). Blood flow of MHD non-Newtonian nanofluid with heat transfer and slip effects: application of bacterial growth in heart valve. *International journal of numerical methods for heat and fluid flow*, *30*(11), 4883–4908. DOI:10.1108/HFF-12-2019-0910

[7] Bhatti, M. M., Elelamy, A. F., Sait, S. M., & Ellahi, R. (2020). Hydrodynamics interactions of metachronalwaves on particulate-liquid motion through a ciliated annulus: application of bio-engineering in blood clotting and endoscopy. *Symmetry*, *12*(4), 532. DOI:10.3390/SYM12040532

[8] Tripathi, D., Prakash, J., Tiwari, A. K., & Ellahi, R. (2020). Thermal, microrotation, electromagnetic field and nanoparticle shape effects on Cu-CuO/blood flow in microvascular vessels. *Microvascular research*, *132*(1), 104065. DOI:10.1016/j.mvr.2020.104065

[9] Bhatti, M. M., Sait, S. M., & Ellahi, R. (2022). Magnetic nanoparticles for drug delivery through tapered stenosed artery with blood based non-Newtonian fluid. *Pharmaceuticals*, *15*(11), 1352. DOI:10.3390/ph15111352

[10] Hosseini-Motlagh, S. M., Samani, M. R. G., & Homaei, S. (2020). Blood supply chain management: robust optimization, disruption risk, and blood group compatibility (a real-life case). *Journal of ambient intelligence and humanized computing*, *11*(3), 1085–1104. DOI:10.1007/s12652-019-01315-0

[11] Meneses, M., Santos, D., & Barbosa-Póvoa, A. (2023). Modelling the blood supply chain. *European journal of operational research*, *307*(2), 499–518. DOI:10.1016/j.ejor.2022.06.005

[12] Rekabi, S., Garjan, H. S., Goodarzian, F., Pamucar, D., & Kumar, A. (2024). Designing a responsive-sustainable-resilient blood supply chain network considering congestion by linear regression method. *Expert systems with applications*, *245*(1), 122976. DOI:10.1016/j.eswa.2023.122976

[13] Hosseini-Motlagh, S. M., Samani, M. R. G., & Faraji, M. (2024). Dynamic optimization of blood collection strategies from different potential donors using rolling horizon planning approach under uncertainty. *Computers and industrial engineering*, *188*(1), 109908. DOI:10.1016/j.cie.2024.109908

[14] Nahofti Kohneh, J., & Teimoury, E. (2016). A model for the design of blood products supply chain at the time of the earthquake disaster considering the transfer from the other provinces (case study: Tehran blood transfusion network). *Industrial management journal*, *8*(3), 487–513. DOI:10.22059/imj.2016.61717

[15] Zahiri, B., Torabi, S. A., Mousazadeh, M., & Mansouri, S. A. (2013). Blood collection management: methodology and application. *Applied mathematical modelling*, *39*(23–24), 7680–7696. DOI:10.1016/j.apm.2015.04.028

[16] Zahiri, B., & Pishvaee, M. S. (2017). Blood supply chain network design considering blood group compatibility under uncertainty. *International journal of production research*, *55*(7), 2013–2033. DOI:10.1080/00207543.2016.1262563

[17] Zhang, Z. H., & Jiang, H. (2014). A robust counterpart approach to the bi-objective emergency medical service design problem. *Applied mathematical modelling*, *38*(3), 1033–1040. DOI:10.1016/j.apm.2013.07.028

[18] Momenitabar, M., Dehdari Ebrahimi, Z., Arani, M., & Mattson, J. (2023). Robust possibilistic programming to design a closed-loop blood supply chain network considering service-level maximization and lateral resupply. *Annals of operations research*, *328*(1), 859–901. DOI:10.1007/s10479-022-04930-x

[19] Yaghoubi, S., Hosseini-Motlagh, S. M., Cheraghi, S., & Gilani Larimi, N. (2020). Designing a robust demand-differentiated platelet supply chain network under disruption and uncertainty. *Journal of ambient intelligence and humanized computing*, *11*(8), 3231–3258. DOI:10.1007/s12652-019-01501-0

[20] Emadi, P., & Pasek, Z. J. (2021). Blood shortage management with a reactive lateral transshipment approach in a local blood supply chain. *Proceedings of the international conference on industrial engineering and operations management* (pp. 319–330). IEOM Society International. DOI: 10.46254/sa02.20210142

[21] Hosseinifard, Z., & Abbasi, B. (2018). The inventory centralization impacts on sustainability of the blood supply chain. *Computers and operations research*, *89*(1), 206–212. DOI:10.1016/j.cor.2016.08.014

[22] Ghahremani-Nahr, J., Nozari, H., & Bathaee, M. (2021). Robust box approach for blood supply chain network design under uncertainty: hybrid moth-flame optimization and genetic algorithm. *International journal of innovation in engineering*, *1*(2), 40–62. DOI:10.52547/ijie.1.2.40

[23] Khojasteh Eghbali, S., Mousavi, S. M., & Salimian, S. (2023). Designing blood supply chain networks with disruption considerations by a new interval-valued fuzzy mathematical model: M/M/C queueing approach. *Computers and industrial engineering*, *182*(1), 109260. DOI:10.1016/j.cie.2023.109260

[24] Karadağ, İ., Keskin, M. E., & Yiğit, V. (2021). Re-design of a blood supply chain organization with mobile units. *Soft computing*, *25*(8), 6311–6327. DOI:10.1007/s00500-021-05618-3

[25] Dehaghani, A. R., Nawaz, M., Sultanie, R., & Quartey-Papafio, T. K. (2021). Mathematical modeling for optimizing the blood supply chain network. *Modern supply chain research and applications*, *3*(3), 174–190. DOI:10.1108/mscra-09-2020-0024

[26] Jabbarzadeh, A., Oghyani, M., & Sadjadi, J. (2015). Provide a robust optimization model for designing the blood supply chain network in crisis situations with regard to reliability. *Quality engineering and management journal*, *5*(2), 85–96.

[27] Hemmelmayr, V., Doerner, K. F., Hartl, R. F., & Savelsbergh, M. W. P. (2009). Delivery strategies for blood products supplies. *OR spectrum*, *31*(4), 707–725. DOI:10.1007/s00291-008-0134-7

[28] Haeri, A., Hosseini-Motlagh, S. M., Ghatreh Samani, M. R., & Rezaei, M. (2020). A mixed resilient-efficient approach toward blood supply chain network design. *International transactions in operational research*, *27*(4), 1962–2001. DOI:10.1111/itor.12714

[29] Hosseini, S. M. H., Behroozi, F., & Sana, S. S. (2023). Multi-objective optimization model for blood supply chain network design considering cost of shortage and substitution in disaster. *RAIRO - operations research*, *57*(1), 59–85. DOI:10.1051/ro/2022206

[30] Mousavi, R., Salehi-Amiri, A., Zahedi, A., & Hajiaghaei-Keshteli, M. (2021). Designing a supply chain network for blood decomposition by utilizing social and environmental factor. *Computers and industrial engineering*, *160*(1), 107501. DOI:10.1016/j.cie.2021.107501

[31] Kohneh, J. N., Teymoury, E., & Pishvaee, M. S. (2016). Blood products supply chain design considering disaster circumstances (case study: earthquake disaster in Tehran). *Journal of industrial and systems engineering*, *9*(special issue on supply chain), 51–72. https://www.jise.ir/article_12911.html

[32] Mohammadian-Behbahani, Z., Jabbarzadeh, A., & Pishvaee, M. S. (2019). A robust optimisation model for sustainable blood supply chain network design under uncertainty. *International journal of industrial and systems engineering*, *31*(4), 475–494. DOI:10.1504/IJISE.2019.099190

[33] Farrokhizadeh, E., Seyfi-Shishavan, S. A., & Satoglu, S. I. (2022). Blood supply planning during natural disasters under uncertainty: a novel bi-objective model and an application for red crescent. *Annals of operations research*, *319*(1), 73–113. DOI:10.1007/s10479-021-03978-5

[34] Eshghi, A. A., Tavakkoli-Moghaddam, R., Ebrahimnejad, S., & Ghezavati, V. R. (2022). Multi-objective robust mathematical modeling of emergency relief in disaster under uncertainty. *Scientia Iranica*, *29*(5), 2670–2695. DOI:10.24200/sci.2020.54485.3770

[35] Eskandari-Khanghahi, M., Tavakkoli-Moghaddam, R., Taleizadeh, A. A., & Amin, S. H. (2018). Designing and optimizing a sustainable supply chain network for a blood platelet bank under uncertainty. *Engineering applications of artificial intelligence*, *71*(1), 236–250. DOI:10.1016/j.engappai.2018.03.004

[36] Rajendran, S., & Ravi Ravindran, A. (2019). Inventory management of platelets along blood supply chain to minimize wastage and shortage. *Computers and industrial engineering*, *130*(1), 714–730. DOI:10.1016/j.cie.2019.03.010

[37] Fallahi, A., Mokhtari, H., & Niaki, S. T. A. (2021). Designing a closed-loop blood supply chain network considering transportation flow and quality aspects. *Sustainable operations and computers*, *2*(1), 170–189. DOI:10.1016/j.susoc.2021.07.002

[38] Soltani, M., Mohammadi, R. A., Hosseini, S. M. H., & Zanjani, M. M. (2021). A new model for blood supply chain network design in disasters based on hub location approach considering intercity transportation. *International journal of industrial engineering and production research*, *32*(3), 1–28. DOI:10.22068/ijiepr.1096

[39] Arani, M., Chan, Y., Liu, X., & Momenitabar, M. (2021). A lateral resupply blood supply chain network design under uncertainties. *Applied mathematical modelling*, *93*(1), 165–187. DOI:10.1016/j.apm.2020.12.010

[40] Haghjoo, N., Tavakkoli-Moghaddam, R., Shahmoradi-Moghadam, H., & Rahimi, Y. (2020). Reliable blood supply chain network design with facility disruption: a real-world application. *Engineering applications of artificial intelligence*, *90*(1), 103493. DOI:10.1016/j.engappai.2020.103493

[41] Hosseini-Motlagh, S. M., Samani, M. R. G., & Cheraghi, S. (2020). Robust and stable flexible blood supply chain network design under motivational initiatives. *Socio-economic planning sciences*, *70*(1), 100725. DOI:10.1016/j.seps.2019.07.001